Competition and Executive Compensation: Evidence from Pharmaceutical Breakthrough Designations

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Abstract

We examine how competition shocks affect executive compensation within the pharmaceutical industry. Specifically, we use Breakthrough Therapy Designations (BTDs) as exogenous shocks to the competitive position of rival pharma-firms operating within the BTD-awarded disease space. We find that rival firms respond by significantly increasing option-based compensation for their CEOs. This adjustment in compensation structure is accompanied by an escalation in the development of new drugs. Our findings support theoretical models suggesting that firms under competitive pressure should intensify innovation and that stock options incentivize executives to pursue such innovation.

Keywords: Executive Compensation; Competition; Options; Incentives

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In the face of heightened competition, firms must adapt their strategies to preserve value. The popular refrain is to innovate. Arrow (1962) develops a theory in which innovation is more beneficial for firms under competitive pressure than in monopolistic conditions, suggesting that firms should increase innovation when competition intensifies. In support, Blundell, Griffiths, and Van Reenen (1999) and Bloom, Draca, and Van Reenen (2016) present empirical evidence that competition spurs innovation. However, risk-averse executives may withhold efforts to boost innovation because "innovation is intrinsically risky and progress more erratic than with standard investments" (Holmstrom, 1989, p. 311). Holmstrom argues that even risk-neutral executives shy away from risky projects and deviate from the standard net present value rules, because they are "carrying (by design) some undiversified risk."

Manso (2011) confronts this concern and studies how incentives should be structured when the principal needs to motivate the agent to increase innovation. He demonstrates that the optimal contract tolerates early failures and rewards long-term success. Unlike standard pay-for-performance schemes, executive stock options meet both criteria. Consequently, Manso (2011) concludes that the optimal contract that motivates innovation includes stock options, whereas standard pay-for-performance schemes may adversely affect innovation. The conclusion aligns with an extensive literature that proposes that options encourage managerial risk-taking, including Jensen and Meckling (1976), Haugen and Senbet (1981), Smith and Stulz (1985), Guay (1999) and Edmans and Gabaix (2011).

Complementing theory, several empirical studies investigate how competition shocks affect executive compensation. One strand of literature, including Hubbard and Palia (1995), Crawford, Ezzell, and Miles (1995), and Cuñat and Guadalupe (2009a), examines banking deregulation as a competitive shock. The collective evidence indicates that banks respond by increasing total pay as well as pay-performance sensitivity, while showing rather modest increases in stock options. Another strand of literature explores competition shocks in international settings. Cuñat and Guadalupe (2009b) report that increases in foreign competition—via tariffs or exchange rate shifts—enhance pay-performance sensitivity. Bakke et al. (2022) study tariff cuts and find that competition reduces risk-incentive pay from stock option grants. Lie and Yang (2022) find that

instrumented import competition from China decreases stock grants but does not affect stock option grants among US manufacturing firms. Overall, there is at best mixed evidence that increases in competition are met with increases in risk-incentive pay by affected firms.

We submit that there are a couple of plausible explanations for the disconnect between past empirical results and the joint prediction of Arrow (1962) and Manso (2011) that competition spurs the use of options to encourage innovation. First, empirical studies might capture more than causal effects. Cuñat and Guadalupe (2009a) study a period of secular shifts in the banking industry as well as the broad economy, either of which are likely culprits to explain compensation policy changes. Relatedly, Lie and Yang (2022) report evidence that changes in tariffs and exchange rates are highly endogenous. Second, past studies focus on the banking and manufacturing sectors, where innovation is a secondary strategic tool. Thus, they are inadvertently rigged against finding changes in risk-incentive pay intended to spur innovation.

We reexamine how competition affects risk-incentive pay using the pharmaceutical sector, which offers an ideal setting for testing the joint predictions of Arrow (1962) and Manso (2011). Innovation is a primary strategic tool in the pharma sector because pharma firms continuously aim to develop products to address unresolved or emerging medical needs, and successful innovations benefit from strong patent protection for numerous years, creating powerful incentives for risk-taking. Furthermore, periodic shocks to competition are common in the pharma sector, as firms successfully develop and launch new products that steal market share from one another. The last decade offers a unique way to identify these shocks and assess their impact on risk-incentive pay.

In 2012, the Food and Drug Administration (FDA) introduced the breakthrough therapy designation (BTD) program, an expedited pathway program designed to facilitate and expedite approval of therapies that demonstrate substantial improvements over existing treatments. BTD events represent significant competitive shocks to *rival* firms, defined here as other firms working in the same therapeutic areas as the BTD-recipient firm (Garfinkel and Hammoudeh (2025)). We further argue that the shocks are exogenous to rivals' compensation structures, as the FDA's decisions are based solely on clinical efficacy and disease severity and no advance signal is given to rival firms.

Armed with a series of BTD shocks scattered across time and therapeutic areas, we examine their impact on the structure of executive compensation at rival firms. Our empirical design further accounts for heterogeneity in rivals' exposure to BTD shocks by identifying *afflicted* rivals. These are defined as the firms competing in the therapeutic area of the BTD that experience the worst abnormal returns following BTD announcements.

Our main analysis examines the effect of BTD shocks on CEO compensation. Difference-in-differences estimates reveal a post-shock divergence in the primary risk-based compensation measures: both the level (value) of option grants and their fraction of total compensation increase for afflicted rival firms relative to control firms in the year after the BTDs. Conversely, stock grants decline while salaries and bonuses remain similar for afflicted rivals compared to control firms after the BTDs. We conclude that BTD shocks prompt afflicted rivals to boost risk-incentive pay.

The most obvious reason for firms to boost risk-incentive pay is to encourage innovation. Thus, we extend our analysis to explore whether rival firms—fortified with the new stock options in the executive rank—shift resources toward riskier innovation. Consistent with Manso (2011), we find that afflicted rivals are more likely to initiate new drug development projects following BTD shocks. Moreover, many of the new projects require new technology or prolonged development and are, therefore, particularly gutsy.

While we cannot establish clear causality between the use of options and risk-taking, our findings suggest that the increase in stock options contributes to riskier development activities. As further support of this interpretation, we show that afflicted rivals with the greatest increases in option compensation (post-BTD), exhibit the most pronounced shift toward riskier drug projects.

Our results are robust to several measurement questions. For example, we offer two alternatives to our main approach of identifying afflicted firms. First, we partition rival firms according to their technological proximity to BTD recipients. The rationale is that rivals employing the same technology as the BTD may experience a boost in their drug's progress. This approach is based on Garfinkel and Hammoudeh (2025), who find that rivals using the same technology as BTD recipients experience benefits from BTD shocks—at least relative to rivals that use a different technology—and continue to pursue their shocked projects. These results suggest that rivals using

the same technology as the BTD are not considered afflicted. Indeed, we find that only rivals utilizing *different* technologies in their own drug projects within the shocked therapeutic area, increase executive stock option use, and they are also the only ones to take on more risky projects.

Our second alternative approach to identifying afflicted rivals is to rank each rival by their relative exposure, calculated as the number of projects that the rival has in the BTD-shocked therapeutic area divided by the rival's total number of drug projects. Thus, if the only drug development projects a firm has are in a single therapeutic area, and that area sees a different firm receive a BTD, the focal firm is considered particularly exposed. Here, too, we find that afflicted rivals respond by raising the option component of executive compensation and increasing risk-taking through new projects and new technologies.

Overall, we report that competitive pressures on pharma firms trigger enhanced risk-taking incentives in the form of increased emphasis on option-based compensation to CEOs. We further find competitive pressure induces riskier drug development projects, especially when option-based compensation increases. Our results dovetail with Arrow's (1962) implication that firms should increase innovation in response to competitive pressure and Manso's (2011) contention that stock options contain the requisite structure to motivate innovative activities. However, our results differ notably from those in other empirical studies of how competition affects compensation structure. We argue that our use of BTDs is a more powerful instrument for establishing a causal effect of competitive pressure on compensation than past studies, for three reasons. First, we argue that our pharmaceutical setting, in which innovation is a first-order strategic activity, is particularly suited to test the combined predictions of Arrow (1962) and Manso (2011). Second, BTDs vary in both the time-series and cross section and are plausibly exogenous to the existing compensation structure of CEOs, unlike prior tests that fixate on policy-based shocks like deregulation. Third, our use of pharma-based innovation measures is more precise than typical R&D.[1] Combined, we contribute to the literature by shedding a skeptical light on prior empirical results, by honing our understanding of competition effects on executive compensation, and by corroborating past theory.

[1] This point is also emphasized by Garfinkel and Hammoudeh (2025), and addresses concerns highlighted in the survey by Frésard and Phillips (2024).

I. The Pharmaceutical Industry Setting and Manso's (2011) Model

A. Institutional Background

The biopharmaceutical industry is well suited for investigating the effect of competition on risk-incentive pay and innovation based on the theoretical frameworks of Arrow (1962) and Manso (2011). First, long-term innovation is crucial to the survival of pharmaceutical firms. Before a firm can market and sell a drug, it must obtain FDA approval. The drug-approval process entails costly and rigorous clinical development to demonstrate both the safety and efficacy of a drug. It can take between 5 and 20 years to obtain FDA approval to market a drug (Brown et al., 2021). In addition, drug development is associated with high uncertainty. Of every 100 drug projects in the preclinical stage (i.e., early in development and focusing on laboratory and animal testing), roughly one project advances and eventually obtains FDA approval (Wouters et al., 2020).[2] As another indicator of high uncertainty and risk, most firms are precommercial without any FDA-approved products, i.e., they only have drug projects under development.[3,4] Finally, after obtaining drug-approval, firms are granted strong patent protection for numerous years. Overall, the pharmaceutical industry rewards long-term successes and has a high incidence of early failures, matching the conditions of Manso (2011).

Second, the market for pharmaceutical drugs is highly competitive. New products are continually developed and successfully launched, causing rival firms to lose market share and perhaps abandon drug development (e.g., Garfinkel and Hammoudeh (2025); Krieger (2021)). Put differently, there is considerable entry and exit across the many therapeutic markets available to pharmaceutical firms. Because of continuous progression and discoveries from development

[2] Furthermore, Hay et al. (2014) estimate that only 10.4% of drugs that reach the first stage of *human* trials (i.e., phase-I clinical trials) are eventually approved.

[3] Technically, the terms *drug* and *drug project* are distinct. A drug can be developed to target several medical conditions, while each drug-medical condition pairing is a drug project. Notably, the FDA approves a drug for a specific medical condition if the drug's human clinical testing results demonstrate its safety and efficacy in treating that medical condition.

[4] In our final sample, 80% of firms had precommercial status at one point in time.

activities, rivals often confront new threats, at which point they may retreat, transition to a new therapeutic area, or fight-back.

Third, breakthrough therapy designations (BTDs) allow us to identify transformational product introductions (i.e., the greatest competitive shocks) at an early stage.[5] The BTD program was established in 2012, allowing the FDA to designate drugs that are "intended to treat a serious condition and that preliminary clinical evidence indicates may demonstrate substantial improvement over available therapies" (Sherman et al., 2013). While the BTD program is the fourth addition to the FDA's expedited approval pathway programs, it tops the ranking of how FDA resources are prioritized (Senior, 2013). Drugs with BTDs benefit from the organizational commitment of FDA senior managers, intensive guidance on efficient drug development programs, and higher likelihood of, and quicker, FDA-approval.[6] Upon approval, BTD drugs are perceived as superior (Krishnamurti et al., 2015; Kesselheim et al., 2016), and anecdotal evidence suggests that they are likely to dominate their therapeutic markets.[7]

Finally, the strict regulatory reporting requirements in the pharmaceutical industry provide detailed descriptions of products and projects, including the target therapeutic market, the target actions (i.e., technology) of drugs, and the progress of projects. This granular description allows us to identify (i) the rival firms in a narrowly defined therapeutic area, which is imperative to our identification strategy, (ii) the extent of a rival firm's exposure to a product market shock, measured in several ways detailed below, and (iii) how rival firms respond *at the project level* to

[5] In fact, BTD drugs are regularly mentioned as sources for significant competition in the financial statements of rival firms. For example, in the 2016 10-K, Bind Therapeutics state "our most significant competition comes from immunotherapies, including nivolumab and pembrolizumab", both of which received a BTD award in 2015. The 2014 10-K of Cocrystal also references Gilead Sciences' two BTD-awarded Hepatitis C treatments, Harvoni and Sovaldi (both of which were designated in 2013), as competitors that significantly changed the competition in the area.

[6] Hwang et al. (2018) find that for a sample of cancer drugs, the median time from Investigational New Drug (IND) application (marking the initiation of human trials) to first FDA approval was 5.2 years for breakthrough-designated drugs, compared to 7.1 years for non-breakthrough-designated drugs. Furthermore, Garfinkel and Hammoudeh (2025) find that BTD drugs are 3 times as likely to receive FDA approval relative to comparable control drugs.

[7] For example, a report published by Vantage in 2018 highlights the growing dominance of Merck's Keytruda in the non-small cell lung cancer therapeutic market. The report states that Keytruda's competitors, "the boat has sailed, and Keytruda has left them fighting over what is at best a vanishingly small slice of the pie."

a product market shock.[8] In short, we can examine the effects of competitive shocks (BTDs) on firms' compensation structure/strategies and their transfer of resources to riskier projects.

B. The Incentives to Exploit vs Explore in Manso (2011)

Manso (2011) begins by analyzing how a single agent chooses between project-execution-methods: a conventional work method (exploitation) and a novel one (exploration). The agent's choice is based on expected payoffs in a two-period model, where learning based on first period outcomes informs second-period choices. With sufficient learning, exploration may yield greater expected payoff than exploitation.

When a principal is introduced, the agent's project-execution-method choice is complicated by the principal's inability to perfectly observe the agent's effort. The principal chooses a compensation contract that encourages exploration (innovation) by providing both (i) protection from failure in the first period and (ii) large upside potential in the case of success in either period to avoid shirking. Option compensation meets both criteria and therefore emerges as a primary tool to encourage innovation.

C. Implications of BTDs for Rivals

BTDs place recipient firms' rivals at a competitive disadvantage. Furthermore, the joint prediction from Arrow (1962) and Manso (2011) is that firms facing enhanced competition respond by awarding more option compensation to the manager to encourage more risk-taking. Combined, the implication is that BTDs trigger rivals to shift toward option-heavy compensation and pivot toward riskier investments. This serves as the foundation for our empirical inquiry.

[8] Johnson & Johnson (JNJ) is one example on how product-level data better identifies firms affected by a market shock, relative to firm-level data, is. According to their 2022 10-K report, JNJ operates in 3 segments: pharmaceutical preparations (which accounted for about 54% of annual revenues), consumer health (16%) and medtech (30%). The Compustat annual files (CRSP) indicates that JNJ's primary SIC code is 2834 (3841), which identifies the pharmaceutical preparations (surgical and medical instruments) industry. This highlights the problems with using firm-level industry classifications to identify affected firms that operate in multiple segments.

A caveat is that Manso (2011) relies on learning by the firm from its *own* project outcomes, while ignoring possible learning from *other* firms' outcomes. BTDs allow rivals to learn from the BTD-recipient's outcome. The FDA's designation of the BTD-receiving drug is based on two main factors: the efficacy over previous therapies and the importance of addressing the disease. Rivals working on drug projects in the same therapeutic area not only observe the designation but also the nature of the drug (including molecule and method of action) due to the reporting requirements of clinical trial stages II and beyond.[9] Thus, rivals obtain significant information about discrete improvements in the treatment of a disease that they are also targeting.

Under certain conditions, the rival's learning from another's BTD may encourage exploitation rather than exploration. The first condition is that the BTD signals potential market expansion of the same therapeutic area that the rival has a project in, as suggested by Garfinkel and Hammoudeh (2025). A second condition is that the rival can participate in the expanding market through the development of a drug with similar efficacy to the BTD. This is more likely when the rival already has a technology (a.k.a. target action) that was just announced as a component of the BTD. Thus, in ancillary analysis, we study the compensation structures of these "same market same technology" (SMST) rivals.

II. Data and Measurement

A. Drug Development, Therapeutic Markets, Target Actions, and BTD Data

Section II.A.1 discusses the details of our drug project data source and drug project ownership. Section II.A.2 describes our definitions of product (i.e. therapeutic) market area and technology-approach. Finally, section II.A.3 gives details on our identification of BTDs.

[9] See Aghamolla and Thakor (2022a) for the effects of the Food and Drug Administration Amendments Act of 2007.

A.1. Drug Development Data

Our drug development data come from Clarivate Cortellis Competitive Intelligence and include pharmaceutical innovation data obtained from company records, conferences, and other public sources. The data has been used in recent studies (e.g., Krieger (2021); Krieger, Li, and Papanikolaou (2021); Hermosilla (2021); Garfinkel and Hammoudeh (2025)). As of the end of 2022, the full sample includes comprehensive development histories and ownership data on over 65,000 drug projects developed by over 7,000 firms targeting over 1,000 medical conditions.

Our sample period is 2010–2022. We focus on drug-indications developed for U.S. markets. We drop drug projects with missing key development dates and "zombie" projects.[10] One challenge with identifying the correct owner of a drug at a certain point in time is that drugs are often acquired or out-licensed. Furthermore, a drug may be developed by a subsidiary of another firm. Therefore, we follow the process from Garfinkel and Hammoudeh (2025) to match each drug project to its correct owner in each year of the sample period.[11]

A.2. Therapeutic Markets and Target Actions

A therapeutic area is the medical condition that a drug is meant to treat. A single drug may be developed for several indications.[12] Cortellis reports all indications a drug is intended to treat, e.g., "Metastatic Breast Cancer." In some cases, two or more indications refer to the same condition, e.g., the indication "liver disease" is likely the same indication as "liver cirrhosis" (Krieger, 2021).[13] To identify potentially competing products within a therapeutic area, we map Cortellis indications to the 10th revision of the International Statistical Classification of Diseases and Related Health Problems classifications (herein ICD-10). We define a *market* by grouping

[10] Firms are often reluctant to report project suspensions. Consistent with Li, Liu, and Taylor (2023), we assume that "zombie" projects are discontinued three years after a "no development reported" designation in the Cortellis data.
[11] Garfinkel and Hammoudeh (2025) conduct an extensive search to identify the correct owner of drugs in the Cortellis data. They use exact and fuzzy matching methods to match firms in Cortellis to firms in the SDC platinum database using firm names. Moreover, they identify subsidiaries using the detailed drug development history descriptions in Cortellis.
[12] We use the terms "medical condition," "indication," "ICD-9 code," and "therapeutic market" interchangeably when referring to the medical condition that is targeted by a drug project.
[13] Approximately 35% of drugs in our data are developed for more than one indication.

drugs with the same ICD-10 code. This process results in 1,009 unique ICD-10 therapeutic markets.[14]

Furthermore, we define the *technology* of a drug based on its molecular target action. The target is the molecule in the body that the drug changes, and the action refers to the type of change. For example, mRNA vaccines work by inducing the muscle cells near the injection site to produce spike proteins similar to those found on the surface of the SARS-CoV-2 virus. This causes the immune system to produce specific antibodies that bind to the spike proteins of the virus and neutralize it. A single drug compound may also have multiple target actions. We identify 6,455 unique target actions in our sample.

A.3. Breakthrough Therapy Designations

We follow Garfinkel and Hammoudeh (2025) to identify BTD events and grant dates. Specifically, we collect information on BTDs from the Friends of Cancer Research (FOCR) website (https://www.focr.org/breakthrough-therapies). FOCR identifies each BTD drug name, the announcement date, the sponsoring firm, and the indications for which the BTD was granted. We manually match the FOCR data to our drug development data using drug names.[15] We validate announcement dates via firm financial statements, FDA disclosures, and business media articles. We also crosscheck our dates with the 143 BTDs in the online supplementary appendix of Hoffmann et al. (2019). Finally, we drop seven BTDs that were rescinded. Our final sample of BTD awards include 405 unique BTDs awarded to 185 firms in 163 ICD-10 markets from December 2012 through December 2021.

[14] We use the more general ICD-10 codes at the first (not second) subchapter level to identify therapeutic markets because we wish to identify all potential rivals before more specifically identifying the most afflicted rivals.
[15] We crosscheck our BTD labels on drugs using the "Regulatory Designation" field in Cortellis, which indicates whether a BTD was granted but does not identify the grant date or the designated drug-indication(s).

B. Executive Compensation Details

We obtain executive compensation details for US firms from Equilar, which provides broader coverage than traditional databases such as ExecuComp and ISS by including smaller publicly traded firms—a critical feature given our focus on the pharmaceutical sector. We collect compensation information for all CEOs during the sample period and exclude observations with invalid executive or firm identifiers. We fixate on CEOs and their compensation given both their primacy as strategic leaders of the companies as well as the extant literature's focus on their compensation structures and incentives.

The objective of this paper is to study the effect of competition shocks on the incentive-related pieces of CEO pay. Our focus is on annual compensation via stock options, stock grants, salary, and total compensation. For each component, we begin by analyzing dollar values (winsorized at the 1st and 99th percentiles to mitigate the influence of outliers). In addition, we examine pay composition, defined as the fraction of total compensation accounted for by option pay, stock pay, and salary, respectively. Analyzing pay composition offers two key advantages: (i) it is less affected by extreme values, and (ii) it effectively captures shifts in firms' incentive strategies, such as substituting options for stock grants to enhance risk-taking incentives.

C. Measures of Rival Risk-Taking through Project Investment

Given the prediction of Arrow (1962) and the setting of Manso (2011), we further seek to measure how rival firms respond to BTD events through their investment behavior, and in particular, whether that investment is more exploratory. We create three rival-investment risk-taking measures that are conceivably more exploratory (than exploitative) in nature. These measures are made possible by the pharmaceutical industry's detailed reporting of drug products and projects. The measures are: new drug project initiation; introduction of new technology not previously used by the rival; and development of a drug with lengthy gestation time for a particular therapeutic market. Notably, the latter two are subsets of the first; they are within the cases of new drug project initiations and have the additional exploratory component (new tech or long

gestation). To align with firm-level compensation analysis, we aggregate project information up to the firm level on a yearly basis.

We begin with the most basic version of drug innovation and identify the years in which a firm begins development of a new project. *Drug Initiation* is an indicator variable that equals one if the firm initiates (begins developing for the first time) a new drug project in the given year. These projects have very low unconditional probabilities of success.[16] Second, we identify whether a new drug project utilizes new technology (i.e., a new target action) that was not previously used by the firm on any of their existing drug projects. The firm's lack of experience with the new technology increases the uncertainty associated with the development's success. *New Tech Initiation* is an indicator (variable) equal to one if the firm starts developing a new drug project with a new technology in the year.

Our final risk-taking measure is based on the length of time a drug project is expected to be under development. Drug development is inherently risky due to high costs, lengthy development times, and low success rates (Hay et al. (2014)). When the time under development is particularly long, perhaps due to the complexity of treatments in that therapeutic area, the risk is heightened correspondingly. We propose that firms pursue projects in markets with lengthy development times in the hopes of obtaining economic rents upon successful completion. Our findings support this theory—markets with longer development times have significantly fewer competing drug projects, and more importantly, fewer approved-for-sale products.[17]

We compute a therapeutic market's average development time by calculating the years required to complete each clinical trial phase (Phase-I, II, or III) for all drug projects in that market, and then summing across the phases, before computing an overall average across all projects within the therapeutic market. *Lengthy Development Initiation* is an indicator variable equal to one

[16] Garfinkel and Hammoudeh (2025) reports average success rates of less than 5%.
[17] Additional analysis confirms these relationships. In untabulated results at the therapeutic market level, we regress both the number of drug projects and the number of approved products on the average development time. Both tests reveal a negative and statistically significant relationship implying that longer development timelines are associated with reduced competition.

if the firm initiates a new drug project in a market where the average development time exceeds the median level in the Cortellis database.

It is worth noting that each of these variables is comprised of drug-level data only available due to the detailed reporting requirements of the industry. While we aggregate drugs and project-level variables to the firm-level, each measure is more granular than typical firm-level proxies for firm risk-taking (e.g., R&D expense in Compustat) and should better capture strategic responses to competitors' BTD events. For example, consider a scenario where a firm responds to a competitor receiving a BTD by reallocating scarce resources from an existing project in the BTD-affected market to a new project employing novel technology (target action) with longer-than-median expected development time. All three of our risk-taking measures would reflect this strategic reallocation. Conversely, aggregated firm measures such as R&D expenditure may not capture this reallocation, as overall expenditures could remain unchanged despite significant resource redistribution.[18]

D. Construction of the Firm-Level and Executive-Level Samples

We study the overlap of firms covered by Cortellis and Equilar for the period of 2010–2022. Importantly, to avoid potential confounding effects of BTD awards on *recipient* firms' compensation decisions, we exclude all observations of BTD recipient firms following the announcement of the BTD grant. We drop foreign firms, observations with non-positive total compensation, and observations without executive titles. Our data requirements yield an initial sample of 5,609 firm-year observations across 840 unique firms with both drug development and executive pay details. Among these firms, we identify 1,380 unique CEOs and base our main analysis on this sample at the executive-firm-year level.[19]

[18] Contrary to our main results and consistent with Garfinkel and Hammoudeh (2025), in untabulated results where we replace the drug-based measures with aggregate measures of R&D expenses, we fail to find a significant relationship between BTD shocks and rival risk-taking. This highlights the benefits of granular data on specific drug-project investments that do not suffer from firm-level aggregation of innovative activities.

[19] This main sample has nearly twice as many unique CEOs as unique firms because of turnover in CEOs.

E. Identifying Afflicted Rivals and Controls

To assess the effect of the BTD award on competitors, we first identify *all* rival firms. We define rival firms as those developing or selling drug therapies in the same therapeutic area as the BTD-recipient drug project. Importantly, these rivals—which do not receive the BTD themselves—experience a suddenly weakened competitive position. For each BTD, the mean (median) number of rivals is 19 (13). We examine rival compensation and risk-taking behavior in the seven-year window around the BTD event (T–3 through T+3, where T represents the BTD award year), with firms considered to be "shocked" in the three years after the BTD event.

Not all rivals are equally impacted by BTD events. For example, rivals that are highly exposed to a shocked market—those with a significant portion of their drug portfolio in that market—are likely more afflicted by the shock, than larger rivals that compete in a diversified set of several markets.[20] Since the objective of our study is to examine the responses of rivals that are most negatively affected (i.e., those whose competitive position is weakened the most), we focus on what we deem to be "afflicted" rivals. We primarily use stock market reactions to identify afflicted rivals; specifically, those rivals with the worst three-day cumulative abnormal returns (CARs) surrounding BTD announcements.[21]

In cases where a rival is hit by multiple BTD events in the same year, we retain only the event that results in the most negative CAR value. This ensures each rival has exactly one BTD shock each year they are shocked. We then sort all rival-year observations into quantiles (halves, terciles, or quartiles) based on CAR values across all years.[22] We designate rivals as *afflicted* in

[20] Nonetheless, it is possible that even large, diversified firms may recognize BTD events as significant game changers and alter their executive compensation practices. Our main approach to determining "afflicted" rivals accounts for this. We also report robustness of our results to classification of afflicted rivals using two alternatives (in section IV.A)

[21] We use a market model with parameters estimated over [−271, −21], relative to the BTD announcement date, and calculate CARs over the three-trading day window [−1, +1], where 0 is the announcement date.

[22] We sort CARs into quantiles regardless of the shock year because we wish to identify the most afflicted rivals over the entire sample period. To see why this is important, consider the alternative of sorting (into quantiles) within-year. This raises the concern that the distribution of BTDs is uneven across years, e.g., more rivals experienced afflicting events in 2015 than in 2013. On the other hand, skeptical readers may worry about potential look-ahead bias. But if this changes the set of afflicted rivals, it is only by excluding an early-shocked-rival that might have made the cut without the extra comparison events. In that case, we bias away from finding our documented results.

year *T* if their corresponding CAR during that year falls into the lowest quantile (across all years of rival CAR reactions).[23] For reference, the average CAR values in the lowest quartile, tercile, and median groupings are –13.1%, –11.7%, and –9.8%, respectively, and the average CAR for all rival firms is –0.25%. Finally, for each afflicted rival, we create seven event-year indicators spanning from three years before to three years after the BTD event year (*T–3, T–2, T–1, T, T+1, T+2,* and *T+3).* [24]

We construct our set of control firms in a similar manner as Garfinkel and Hammoudeh (2025). They consist of three groups of firms: (i) those that never experience BTD entry in any of the markets where they operate, (ii) those that eventually experience an afflicting BTD entry event but not as of the focal year (i.e., they only become afflicted rivals as later-treated firms), or (iii) those that actively experience BTD entry, but that were relatively less affected (as determined by the stock market reactions) by the BTD announcement.[25] Finally, we exclude afflicted rivals from either (treated or control) sample three years after they experience an afflicting BTD event, to control for the early treatment problem highlighted in Baker et al. (2022).

F. Sample Descriptive Statistics

Table I presents summary statistics on the main variables used in the analysis. Panel A summarizes the CEO compensation variables. On average, CEOs earn about $3.3 million per year. Options represent the largest component, averaging nearly $1.5 million, while stock grants and

[23] If a rival experiences multiple afflicting BTD events in consecutive years, then we retain the very first one and disregard the others.

[24] We recognize that firms may set executive compensation plans for the new year shortly after their fiscal year end, which is December for roughly 95% of the sample firms. Thus, we make one adjustment to ensure that the timing of a BTD shock is included in the compensation package. Specifically, we count BTD shocks that occur in January, February or March of year T as a shock for the firm in year T–1, as the firm likely has time to incorporate that BTD shock in year T's compensation package.

[25] In Table A2, we replicate our main compensation tests using a synthetic sample that is constructed by matching each afflicted rival to a specific control. We first develop a pool of control firms within the same size decile as the focal (afflicted) firm and with the same precommercial status, where size is measured as the total number of drug projects owned by the firm. Then we randomly select one control firm to make each match one-to-one.

base salary average $675,000 and $493,000, respectively. On average, options account for 37% of total compensation, highlighting their central role in incentivizing CEOs in our sample.

Panel B of Table I summarizes the risk-taking measures. Approximately 39% of the firm-year observations involve the initiation of new drug development, suggesting that such innovative activities are relatively common in the sample. Although less common, some drug initiations require a new technology that was not previously used by the firm (34%). Also less common are drug initiations in markets with lengthy development times (27%).

III. Empirical Design and Results

The objective of the paper is to test whether heightened competition encourages firm innovation and ascertain whether firms adjust their executive compensation structure to facilitate this. Section A focuses on the more-readily identifiable effect of competitive shocks on executive compensation changes. Section B explores whether innovative investment is thereby encouraged.

A. Executive Compensation around BTD Events

This section lays out our testing approach and results on how shocks to a firm's competitive position influence its compensation structure. The general form is discussed in III.A.1. We address measurement of parallel trends in III.A.2. Treatment effects are described in III.A.3.

A.1 General Model

We examine the effect of BTD shocks on the structure of executive compensation at rival firms using difference-in-differences (DiD) regressions. This analysis compares afflicted rivals to control firms before and after the BTD events. We run the following general model via OLS:

$$Compensation_{e,f,t} = \sum_{n=-3}^{n=3} \beta_n Rival\ Year\ (T+n)_{f,t,s} + X_{f,t} + \emptyset_f + \gamma_t + \varepsilon_{e,f,t} \qquad (1)$$

where *e* indexes executive, *f* indexes firm, *t* indexes calendar year, and *s* indexes BTD shock vintage year. The dependent variable, *Compensation,* is measured in both levels and percentages. The component percentage variable is calculated as the percentage of executive *e*'s total

compensation that is in a given component in year *t*. *Rival Year* is the main independent variable of interest. We examine compensation variation centered around the BTD event which occurs in year T by including the *Rival Year* indicator variables *(T–3, T–2, T–1, T+1, T+2,* and *T+3)*, where T is the BTD event year for the afflicted rival.[26]

$X_{f,t}$ represent time-varying firm controls that are commonly found in the extant pharma-finance literature. *Precommercial* is an indicator variable equal to one for firms with no approved projects (as yet). It is a blunt instrument to proxy shifting success and likely ability to tap capital markets (rising once the firm has an approved-for-sale drug product). *Firm total projects* measures the number of current projects the firm has (including both approved and currently under development). It is a commonly used proxy for pharma-firm size (e.g., in Aghamolla and Thakor (2022b)). $\emptyset_f$ are firm fixed effects, and γ_t are year fixed effects. We cluster standard errors at the firm level.

A.2 Parallel Trends

Before drawing causal inferences, DiD estimations require that the parallel trends assumption be satisfied. In our context, executive pay should not appear significantly different between afflicted firms and control firms *before* the BTD shock. The corollary is that we do not expect to see noticeable differences between afflicted and control firms until after the shock occurs.

We run the OLS regressions in equation (1) and examine the coefficients on the *Rival Year* indicators in the three years before the shock. The coefficients on *Rival Year* capture the differential compensation between afflicted rivals and controls. If these are not reliably different from zero in the years before the shock year, parallel trends are possible. Table II and Table III report results using compensation levels, and compensation component percentages, respectively. For Table II, given the nonnegative values and high incidence of zeros in the compensation components, we estimate fixed-effects Poisson regressions, consistent with recent empirical

[26] The BTD event occurs in year T, which serves as the omitted baseline period for comparison. In un-tabulated results, we re-estimate our tests and use Year T–1 as the base group and find similar results.

finance literature (e.g., Cohn et al., 2022; Haslag et al., 2024; Gerken et al., 2025).[27] Those results are robust to log-transformations, as shown in Appendix Table A1.

In most cases, the coefficients for *Rival Years* preceding the BTD are statistically insignificant. The exceptions are when rivals are defined as afflicted using the broadest categorization, i.e., CAR worse than the median CAR across the entire sample. For the narrower definitions of afflicted rivals on which we place more confidence, we find no violation of the parallel trends assumption.

A.3 Treatment Effects

Table II also documents the *post-event* effects of BTD shocks on the main measures of CEO compensation. The dependent variable in Panels A-D is respectively: the level of option awards; stock grants; salary; and total compensation. Panel A reports the 'levels-version' of our main result supporting Arrow (1962) and Manso (2011). Afflicted rivals respond to the BTD by significantly increasing the risk-incentive pay of CEOs in the first year immediately after the shock. Furthermore, as we define afflicted rivals more stringently, we observe larger coefficients and observed adjustments in risk-incentive pay, consistent with a greater need to encourage innovation as competitive position worsens. The coefficient magnitudes are economically significant; examining the first column of Panel A in Table II, afflicted rivals increase stock option compensation by approximately 17% (calculated as $(e^{0.154} - 1) \times 100 = 16.6\%$) in the year after a BTD shock, relative to control firms.

It is important to contrast the results in Panel A (options award levels) with those in Panel B (stock grants), which show a substantial decline. This is especially true for more afflicted rivals, where the parallel trends are clearer. Severe BTD shocks are associated with sharp shifts in compensation structure: pay-for-performance incentives weaken while risk-taking incentives strengthen. This pattern aligns with the joint predictions of Arrow (1962) and Manso (2011).

[27] We implement this approach using the PPMLHDFE package (Correia et al., 2020). Unlike the log-linear model, this method provides a natural way to deal with zero values on the dependent variable while also allowing for high-dimensional fixed effects.

Table III reinforces the shift in compensation structure by presenting OLS results using compensation component percentages as the dependent variables, rather than levels. The findings mirror those in Table II in three key ways. First, in the year following a BTD shock, afflicted rivals increase the percentage of options in CEO pay packets relative to control firms. Second, the magnitude of this effect grows as the definition of affliction is narrowed (i.e., tercile and quartile sorts vs. median). Third, afflicted rivals reduce stock-based pay following a BTD shock, reallocating compensation toward instruments that reward exploratory effort. Taken together, the results suggest that afflicted rivals view increased risk-taking as an appropriate response to competitive pressure and adjust CEO incentives accordingly. The next section examines rival risk-taking following BTD shocks.

B. Rival Risk-Taking around BTD Events

Given our evidence of rival-firm adjustments to risk-incentive pay following BTD shocks, we now explore whether afflicted rivals subsequently pursue riskier projects. We specifically estimate the effect of BTD shocks on rivals' risk-taking using difference-in-differences (DiD) OLS regressions, via the following model:

$$Risk_{f,t} = \sum_{n=-3}^{n=3} \beta_n Rival\ Year\ (T+n)_{f,t,s} + \emptyset_f + \gamma_t + \varepsilon_{f,t} \quad (2)$$

where *f* indexes firm, *t* indexes calendar year, and *s* indexes BTD shock vintage year. The sample consists of all rival firm-years with available compensation data and drug development data. The dependent variable, *Risk,* is one of (in each regression) the three indicators that proxy for risk-taking described in Section II.C. *Rival Year* is the main independent variable of interest. We again have seven *Rival Year* indicators, one for each of the seven years centered around the year of the BTD shock. The indicator values equal one for shocks that correspond with the rival being afflicted, zero otherwise (i.e., control observations). $\emptyset_f$ are firm fixed effects, and γ_t are year fixed effects. Standard errors are clustered at the firm level.

Once again, the regression model in equation (2) effectively serves as a test for the parallel trends assumption. If this assumption holds, we expect the coefficients on the rival year indicators

to *not* be statistically significant in the three years *before* the shock year, which we do observe. Therefore, any differences that appear after the shock are unlikely to be a continuation of a trend.

Table IV reports the results from OLS regressions of firm risk-taking on shock year indicators. In Panel A, the dependent variable is the *Drug Initiation* indicator. The results suggest that afflicted rivals are significantly more likely to initiate a new drug project in the first year after the shock. Furthermore, rivals that were more afflicted by the shock (defined on quartile sorts) are more likely to initiate a drug project relative to less afflicted rivals (defined on median sorts).

Panels B and C continue to support the interpretation that firms respond to shocks with more innovation. In B, with *New Technology* initiations as the dependent variable, we again observe that afflicted rivals, especially those highly afflicted by the shock, are significantly more likely to initiate drug projects that use new technology, in the first year after being shocked. In C, the *Lengthy Development Time* dependent variable increases in the first year post-BTD shock. We also observe a higher propensity for more afflicted (upper tercile and quartile) rivals to initiate projects in markets with lengthy development times. In summary, the results in this section provide evidence in favor of increased risk-taking by afflicted rivals, and the effect is proportional to the extent of affliction.

Finally, we explore whether larger post-shock option grants associate with the documented increase in innovative investment post-shock. To do so, we re-estimate equation (2) but with three adjustments. First, we consolidate the *Rival Year* indicators [+1 through +3] into a simple post-shock dummy (*Post*). Second, we include an interaction between *Post* and *Option_increase*, where *Option_increase* captures the percentage change in a CEO's option compensation from the three-year pre-shock period to the three-year post-shock period.[28] Third, we restrict the sample to the most afflicted rivals—those in the bottom quartile of CARs around the BTD shock.

Table V reports the results. The *Post* stand-alone effect is economically small and statistically insignificant, indicating no systematic shift in risk-taking among highly afflicted firms that leave option grants unchanged. By contrast, the *Post x Option_increase* coefficient is positive

[28] We also include *Option*_increase and *Post* as stand-alone controls.

and significant, showing that severely afflicted rivals awarding larger option increases also undertake markedly more risky projects. Although these tests do not definitively identify option increases as the causal driver of riskier project choices, they provide further support for the joint hypotheses of Arrow (1962) and Manso (2011).

IV. Robustness

We conduct three sets of robustness tests to underline our results and conclusions. The first set addresses our classification approach for afflicted rivals. The second replaces the Poisson estimation with simple OLS and an adjusted dependent variable construction. The third more tightly matches control firms with treated ones for estimation of the DiD. All of these adjustments fail to undermine our conclusions.

A. Alternative Definitions for Afflicted

We redefine afflicted rivals using two different perspectives on "exposure" to the shock. First, we define rivals based on the technology used in their drug projects relative to the BTD awarded drug within the same therapeutic market. We distinguish between two groups: (i) *Same Market Different Technology* (SM) rivals, which operate in the same therapeutic area but employ a different technology as the BTD drug; and (ii) *Same Market Same Technology* (SMST) rivals, which employ the same technology as the BTD drug.[29] While SM rivals are placed at a clear disadvantage because of their use of an 'outdated' technology, SMST rivals find themselves more closely aligned as they share the technology that was designed as 'superior' by the FDA.[30]

Second, we classify afflicted rivals based on shock exposure, defined as the fraction of a firm's portfolio (number of projects) that is in the shocked product market. Under this definition,

[29] For example, in the Hepatitis C market, Gilead Sciences's drug Harvoni was awarded a BTD designation. Harvoni's technology acts by interfering with the NS5A protein. Competitor drugs that use this technology to target Hepatitis C are considered SMST rivals, whereas competitors using the older interferon technology are considered SM rivals.
[30] Garfinkel and Hammoudeh (2025) find that SMST rivals display significantly more positive announcement returns relative to SM rivals and are more likely to develop their SMST projects and eventually bring them to the market.

a firm is considered to be more afflicted if its exposure falls in the upper half (or top tercile/quartile) of the distribution.

We re-estimate the main regressions from Tables II–IV using these alternative classifications. Tables VI–IX present the results. Consistent with expectations, SM rivals—those most technologically displaced—exhibit significant increases in both option-based compensation and risk-taking behavior following the BTD shock. Likewise, firms with greater exposure to shocked markets respond similarly to afflicted rivals defined using announcement returns. Across all definitions of affliction, we find evidence that rivals respond to competitive shocks by reallocating compensation toward stock options. These robustness tests reaffirm our central finding: rival firms systematically increase option-based pay in response to competitive shocks, consistent with theoretical predictions that stock options are the optimal contract for inducing innovation under heightened competition.

B. OLS Estimation of Option Award Levels Regressions

The Poisson technique is well-suited for handling skewed distributions that are commonly found in executive compensation studies. Nonetheless, we also employ OLS estimation, focusing on option awards with a simple log transformation, in which we calculate the dependent variable as the logarithm of (1+option award). Table A.1 reports results, and they confirm our original conclusions. The coefficient on *Rival Year (T+1)* is positive and significant across all three levels of affliction (of rivals).

C. Tighter Control Matching

We revise our DiD to distinguish more carefully the cross-sectional differential, by selecting a closely matched control firm for each treated firm. We first create a pool of all potential control firms by matching each BTD-shocked firm to all control firms in the same size decile and with the same precommercial status. Size is measured as the total number of projects owned by a firm in a given year. Moreover, we ensure that control firms have at least the same number of years in

sample as the focal treatment firm. Next, if more than one control firm results from the match, we randomly select one to make it a one-to-one match. This results in matching 450 treatment firms to 300 control firms.[31]

Again our results from Tables II and III are confirmed in Table A2. Option compensation rises and stock compensation falls, after BTD shocks at afflicted firms. We conclude that our results are not sensitive to control firm selection.

V. Conclusion

We study how firms adjust executive compensation structure in response to competitive shocks. Based on the theories of Arrow (1962) and Manso (2011), the optimal firm response to heightened competition is to increase innovation, which can be encouraged through greater risk-incentive pay. But empirical work in the compensation literature fails to support this prediction. We offer a new approach and new results.

Our analysis focuses on the pharmaceutical industry. This focus carries several advantages, including (i) highly innovation-oriented investments, (ii) detailed investment activity data, and (iii) a set of time-varying cross-sectional shocks to firms' competitive positions in the form of Breakthrough Therapy Designations (BTDs). The BTDs signal the FDA's favorable view of the potential for a drug under development, and they expedite the FDA approval process. As a result, rival firms, i.e., those that have competing drug projects with the one that received the BTD, suddenly find themselves at a competitive disadvantage and need to adjust.

We show that BTD-shocked rivals swiftly and significantly increase their risk-incentive pay after the shocks. In addition, they pivot their drug development projects in new and riskier directions. Combined, our results are consistent with the aforementioned theories for how firms should optimally respond in the face of increased competition.

[31] Note that a control firm may appear more than once in a single year if it is matched to more than one treatment firm. This is why the sample size for the tests in Table A2 is larger than that of Tables II and III.

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Table I: Summary Statistics

This table provides summary statistics for the variables used in later analyses. The sample consists of 840 publicly listed firms from 2010 through 2022 and excludes observations of firms that receive a BTD award from the first award year to the end of the sample period.

Panel A reports the average values of the afflicted rival-year indicators. For columns 1, 2, and 3, the column headings indicate whether an afflicted rival has an announcement return around a BTD event that is in either the lower half ("Median"), lowest tercile ("Tercile"), or lowest quartile ("Quartile") of all rival announcement returns around all BTD events in all years. Rival Year (T±N) is an indicator defined at the firm-level and equals one in year (T±N) relative to the year the rival experienced the afflicting BTD event.

Panel B reports the average values for the executive compensation of the 1,380 CEOs of firms in our sample. Compensation levels are the dollar amount for each component of compensation, whereas the percentages are scaled by total compensation. All compensation variables are winsorized at the 1st and 99th percentiles. *Precommercial* is a dummy equal to one if the firm has no approved for sale products and equal to zero if at least one of its products has been FDA approved. *Total Drug Projects* is the total number of drug projects owned by a firm in a given year.

Panel C reports statistics for the risk-taking measures. These variables are first constructed using the drug-level records in the Cortellis database and then aggregated to the firm-level. *Drug Initiation* is an indicator calculated each firm-year that equals one in the years when a firm starts developing a drug project. *New Tech Initiation* is an indicator that equals one in the years when a firm starts developing a drug project and that new project uses a technology (i.e., target-based action) that the firm has not used before. *Lengthy Development Initiation* is an indicator that equals one in the years that a firm starts developing a new project and that new project targets a therapeutic market that has an average development time above the median level in the Cortellis database. Development time is the average time spent by drug projects in a therapeutic market to complete clinical trials and receive FDA approval.

Panel A: Descriptive Statistics on Compensation and Control Variables

	Mean	Median	SD
Options	1,490,305	642,803	2,023,545
Stock	674,905	0	1,499,780
Salary	492,571	491,667	231,462
Total Compensation	3,295,933	1,855,626	3,704,253
Option %	0.369	0.365	0.299
Stock %	0.118	0.000	0.199
Salary %	0.315	0.237	0.249
Precommercial	0.773	1	0.418
Total Drug Projects	20.989	12.500	47.839

Panel B: Descriptive Statistics on Risk-Taking Variables

	Mean	Median	SD
Drug Initiation	0.386	0.000	0.487
New Tech Initiation	0.336	0.000	0.473
Lengthy Development Initiation	0.269	0.000	0.444

Table II: CEO Compensation Levels Around BTD Grants

This table examines how BTD shocks affect CEO compensation levels at rival firms. The table presents coefficients from Poisson Pseudo-likelihood regressions using equation (1). The dependent variables are the level of stock options (Panel A), stock grants (Panel B), salary (Panel C), and total compensation (Panel D). Control variables include the *Precommercial* dummy and the natural log of drug projects owned by a firm. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
	Panel A: Options		
	(1)	(2)	(3)
Rival Year –3	–0.275*	–0.130	–0.037
	(–1.954)	(–0.946)	(–0.274)
Rival Year –2	–0.212*	–0.050	–0.044
	(–1.766)	(–0.530)	(–0.479)
Rival Year –1	0.018	–0.112	–0.017
	(0.243)	(–1.540)	(–0.215)
Rival Year +1	0.154***	0.162***	0.198***
	(2.681)	(2.742)	(3.240)
Rival Year +2	0.128**	0.080	0.010
	(2.272)	(1.277)	(0.141)
Rival Year +3	0.034	0.090	0.112
	(0.510)	(1.252)	(1.530)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
	Panel B: Stock		
	(1)	(2)	(3)
Rival Year –3	–0.326*	–0.299	0.030
	(–1.796)	(–1.438)	(0.156)
Rival Year –2	–0.324	–0.291	–0.068
	(–1.550)	(–1.486)	(–0.387)
Rival Year –1	–0.274*	–0.121	–0.040
	(–1.766)	(–0.736)	(–0.235)
Rival Year +1	–0.089	–0.297**	–0.394***
	(–0.805)	(–2.411)	(–3.014)
Rival Year +2	–0.123	–0.261**	–0.212*
	(–1.218)	(–2.392)	(–1.671)
Rival Year +3	–0.038	0.078	0.049
	(–0.369)	(0.697)	(0.399)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
	Panel C: Salary		
	(1)	(2)	(3)
Rival Year –3	0.026	–0.015	–0.007
	(1.012)	(–0.517)	(–0.231)
Rival Year –2	0.007	–0.007	–0.000
	(0.308)	(–0.308)	(–0.008)
Rival Year –1	0.037	0.040	0.064
	(1.077)	(1.168)	(1.610)
Rival Year +1	0.077	0.054	0.075
	(0.874)	(1.226)	(1.116)
Rival Year +2	0.029*	0.032*	0.043*
	(1.811)	(1.746)	(1.726)
Rival Year +3	0.070	0.046	0.028
	(0.948)	(1.394)	(1.403)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
	Panel D: Total Compensation		
	(1)	(2)	(3)
Rival Year –3	–0.172**	–0.113	–0.029
	(–2.037)	(–1.306)	(–0.346)
Rival Year –2	–0.140**	–0.014	–0.004
	(–2.007)	(–0.208)	(–0.056)
Rival Year –1	0.000	–0.077	–0.021
	(0.007)	(–1.345)	(–0.360)
Rival Year +1	0.049	0.026	0.059
	(1.192)	(0.594)	(1.295)
Rival Year +2	0.017	–0.031	–0.042
	(0.438)	(–0.761)	(–0.878)
Rival Year +3	–0.014	0.045	0.066
	(–0.339)	(0.983)	(1.307)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579

Table III: Executive Compensation Composition Around BTD Grants

This table examines how BTD shocks affect the composition of CEO compensation at rival firms. Specifically, it presents coefficients on the event-year indicators from OLS regressions estimated using equation (1), where the dependent variable is the percentage of total compensation allocated to options (Panel A), stock (Panel B), and salary (Panel C), respectively. All regressions include firm and year fixed effects, as well as control variables from Table II. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
	Panel A: Options %		
	(1)	(2)	(3)
Rival Year –3	–0.069*	–0.034	–0.025
	(–1.926)	(–1.333)	(–0.915)
Rival Year –2	–0.037*	–0.013	–0.025
	(–1.677)	(–0.634)	(–1.163)
Rival Year –1	0.001	–0.002	–0.001
	(0.074)	(–0.090)	(–0.031)
Rival Year +1	0.029*	0.052***	0.053***
	(1.889)	(3.212)	(3.162)
Rival Year +2	0.022	0.016	–0.012
	(1.439)	(1.003)	(–0.707)
Rival Year +3	–0.001	–0.008	–0.003
	(–0.045)	(–0.443)	(–0.175)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
R-squared	0.388	0.388	0.388

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
	Panel B: Stock %		
	(1)	(2)	(3)
Rival Year –3	0.009	–0.005	0.023
	(0.628)	(–0.342)	(1.621)
Rival Year –2	–0.004	–0.023	–0.003
	(–0.340)	(–1.518)	(–0.185)
Rival Year –1	–0.001	–0.008	–0.009
	(–0.110)	(–0.711)	(–0.743)
Rival Year +1	–0.006	–0.027***	–0.034***
	(–0.638)	(–2.715)	(–3.563)
Rival Year +2	–0.004	–0.018*	–0.024**
	(–0.449)	(–1.775)	(–2.307)
Rival Year +3	–0.003	–0.006	–0.016
	(–0.245)	(–0.488)	(–1.348)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
R-squared	0.514	0.514	0.515
	Panel C: Salary %		
	(1)	(2)	(3)
Rival Year –3	0.054*	0.033	0.020
	(1.778)	(1.604)	(0.968)
Rival Year –2	0.030*	0.024	0.023
	(1.717)	(1.357)	(1.222)
Rival Year –1	0.028*	0.037	0.037
	(1.839)	(1.494)	(1.368)
Rival Year +1	0.010	0.007	0.002
	(0.879)	(0.587)	(0.191)
Rival Year +2	0.004	0.021*	0.034**
	(0.338)	(1.701)	(2.429)
Rival Year +3	0.018	0.020	0.020
	(1.529)	(1.482)	(1.323)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
R-squared	0.460	0.461	0.460

Table IV: Risk-Taking following BTD shocks

This table presents OLS regression results examining the effect of afflicting BTD events on the risk-taking activities of rival firms, based on the specification in equation (2). In Panel A, the dependent variable, *Drug Initiation*, is an indicator equal to one in years when a firm begins developing a drug project for the first time. In Panel B, the dependent variable, *New Tech Initiation*, equals one in the years when a firm initiates a new drug project that uses a technology (e.g., target-based action) not previously used by the firm. In Panel C, the dependent variable, *Lengthy Development Initiation*, equals one in years when a firm starts developing a new project not previously used by the firm that targets a therapeutic market with an average development time—measured as the time from clinical trials to FDA approval—that is above the median level in the Cortellis database. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
Panel A: Drug Initiation			
	(1)	(2)	(3)
Rival Year –3	0.055	0.086	0.104
	(1.471)	(0.187)	(0.707)
Rival Year –2	0.037	0.035	0.019
	(1.208)	(0.971)	(0.566)
Rival Year –1	0.063	0.083	0.069
	(1.232)	(1.494)	(1.248)
Rival Year +1	0.065**	0.090***	0.100***
	(2.523)	(2.864)	(3.544)
Rival Year +2	0.024	0.028	–0.011
	(0.849)	(0.840)	(–0.355)
Rival Year +3	–0.017	–0.071	–0.076
	(–0.549)	(–0.927)	(–1.208)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,067	5,067	5,067
R-squared	0.510	0.511	0.513

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
Panel B: New Tech Initiation			
	(1)	(2)	(3)
Rival Year –3	0.019	0.049	0.022
	(0.571)	(1.301)	(0.546)
Rival Year –2	0.005	0.001	–0.019
	(0.171)	(0.040)	(–0.554)
Rival Year –1	0.041	0.040	0.035
	(1.406)	(1.251)	(1.025)
Rival Year +1	0.039	0.079***	0.083***
	(1.552)	(2.691)	(2.851)
Rival Year +2	0.048*	0.003	0.016
	(1.735)	(0.103)	(0.484)
Rival Year +3	–0.017	–0.050	–0.050
	(–0.544)	(–1.425)	(–1.340)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,067	5,067	5,067
R-squared	0.455	0.456	0.456
Panel C: Lengthy Development Initiation			
	(1)	(2)	(3)
Rival Year –3	0.005	0.049	0.070
	(0.120)	(1.169)	(1.628)
Rival Year –2	0.056*	0.108	0.142
	(1.716)	(1.150)	(0.956)
Rival Year –1	0.036	0.044	0.061
	(1.208)	(1.365)	(0.792)
Rival Year +1	0.025	0.058*	0.061*
	(0.898)	(1.941)	(1.885)
Rival Year +2	–0.033	–0.033	–0.022
	(–1.178)	(–1.055)	(–0.619)
Rival Year +3	–0.054*	–0.070	–0.030
	(–1.680)	(–1.012)	(–0.820)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,067	5,067	5,067
R-squared	0.441	0.443	0.443

Table V: Risk-Taking following BTD shocks

This table reports regression results examining the effect of increased option compensation on firm risk-taking. Each column restricts the sample to a specific subset of rivals—for example, columns 1, 4 and 7 include only afflicted rivals with announcement returns in the bottom half of the distribution. *Post* is a binary variable equal to one for each of the three years following the BTD shock. *Option_increase* is the percentage change in the average share of pay in options from the three years before to the three years after the shock. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Drug Initiation			New Tech Initiation			Lengthy Development Initiation		
Rival Definition	Median	Tercile	Quartile	Median	Tercile	Quartile	Median	Tercile	Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post	–0.002	–0.004	–0.000	–0.002	–0.005	–0.004	0.000	–0.003	–0.002
	(–0.599)	(–0.903)	(–1.616)	(–0.556)	(–1.305)	(–1.152)	(0.137)	(–1.001)	(–0.599)
Post*Option_increase	0.034**	0.040***	0.062***	0.023	0.034*	0.037*	0.011	0.027*	0.032*
	(1.957)	(2.664)	(3.482)	(1.523)	(1.753)	(1.880)	(0.538)	(1.670)	(1.735)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,185	1,921	1,736	2,185	1,921	1,736	2,185	1,921	1,736
R-squared	0.369	0.366	0.364	0.393	0.381	0.380	0.430	0.415	0.415

Table VI: Executive Compensation and SM and SMST Rivals

This table presents regressions of executive compensation on BTD rival event years. SM rivals are defined as rivals that operate in the same therapeutic market as the BTD drug but use different technology. SMST rivals are defined as rivals that operate in the same therapeutic market and use the same technology as the BTD drug. Panel A reports results using the level of stock option pay as the dependent variable. Panel B reports results using the percentage of option compensation as the dependent variable. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Options

	(1)	(2)	(3)
SMST Y–3	–0.199		–0.157
	(–1.574)		(–1.238)
SMST Y–2	–0.302***		–0.030
	(–2.875)		(–0.317)
SMST Y–1	–0.089		–0.152
	(–0.850)		(–1.548)
SMST Y+1	–0.243***		0.111
	(–2.888)		(1.374)
SMST Y+2	–0.123		0.096
	(–1.556)		(1.268)
SMST Y+3	0.041		–0.143
	(0.564)		(–1.543)
SM Y–3		–0.053	–0.458
		(–0.436)	(–0.815)
SM Y–2		0.112	–0.547
		(1.072)	(–1.323)
SM Y–1		–0.020	–0.368
		(–0.223)	(–0.933)
SM Y+1		0.147*	0.142*
		(1.946)	(1.824)
SM Y+2		0.147**	0.145**
		(2.003)	(2.434)
SM Y+3		–0.088	–0.155
		(–0.946)	(–1.611)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,007	5,007	5,007

Panel B: Option %			
	(1)	(2)	(3)
SMST Y–3	–0.020		–0.022
	(–0.735)		(–0.831)
SMST Y–2	–0.009		–0.011
	(–0.320)		(–0.420)
SMST Y–1	–0.016		–0.013
	(–0.680)		(–0.542)
SMST Y+1	–0.007		–0.008
	(–0.366)		(–0.404)
SMST Y+2	0.031		0.029
	(1.625)		(1.455)
SMST Y+3	–0.023		–0.033
	(–1.017)		(–1.484)
SM Y–3		–0.030	–0.032
		(–1.199)	(–1.620)
SM Y–2		–0.028	–0.041
		(–1.275)	(–1.174)
SM Y–1		–0.036	–0.035
		(–1.602)	(–1.586)
SM Y+1		0.058***	0.036*
		(2.697)	(1.818)
SM Y+2		0.033*	0.021
		(1.735)	(1.372)
SM Y+3		–0.007	–0.006
		(–0.418)	(–0.381)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,007	5,007	5,007
R-squared	0.378	0.387	0.381

Table VII: Risk-Taking and SM and SMST Rivals

This table presents OLS regressions of firm risk-taking on BTD rival event years. SM rivals are defined as rivals that operate in the same therapeutic market as the BTD drug but use a different technology. SMST rivals are defined as rivals that operate in the same therapeutic market and use the same technology as the BTD drug. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Drug Initiation			New Tech Initiation			Lengthy Development Initiation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SMST Y–3	0.004		0.132	0.004		0.065	0.194		0.370
	(0.013)		(0.422)	(0.021)		(0.341)	(0.544)		(0.872)
SMST Y–2	–0.307		–0.322	–0.302		–0.287	–1.268		–1.176
	(–0.915)		(–0.981)	(–1.198)		(–1.188)	(–1.420)		(–1.407)
SMST Y–1	0.199		0.271	0.088		0.162	–0.426		–0.281
	(0.638)		(0.864)	(0.463)		(0.876)	(–0.980)		(–0.763)
SMST Y+1	–0.081		0.027	0.002		0.075	–0.465		–0.343
	(–0.361)		(0.116)	(0.015)		(0.616)	(–1.567)		(–1.366)
SMST Y+2	–0.383*		–0.430**	–0.192		–0.171	–0.568**		–0.579**
	(–1.951)		(–2.136)	(–1.581)		(–1.403)	(–1.974)		(–2.038)
SMST Y+3	–0.230		–0.197	–0.219**		–0.196*	–0.358		–0.338
	(–1.143)		(–0.961)	(–2.083)		(–1.814)	(–1.640)		(–1.568)
SM Y–3		–0.744	–0.799		–0.685	–0.713		–1.908	–1.940
		(–1.547)	(–1.556)		(–1.206)	(–1.255)		(–1.513)	(–1.612)
SM Y–2		0.940	0.971		–0.116	–0.096		–0.753	–0.648
		(1.378)	(1.646)		(–0.433)	(–0.369)		(–0.999)	(–0.940)
SM Y–1		–0.212	–0.263		–0.479	–0.516		–0.619	–0.613
		(–0.480)	(–0.583)		(–1.085)	(–1.236)		(–1.069)	(–1.074)
SM Y+1		0.068**	0.053*		0.036*	0.032*		0.027*	0.025
		(2.185)	(1.878)		(1.888)	(1.700)		(1.729)	(1.382)
SM Y+2		0.046*	0.040		0.013	0.008		0.007	0.042
		(1.755)	(1.141)		(1.109)	(1.011)		(0.019)	(0.108)
SM Y+3		0.181	0.178		0.082	0.095		0.089	0.084
		(0.447)	(0.434)		(0.325)	(0.373)		(0.289)	(0.268)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,958	4,958	4,958	4,958	4,958	4,958	4,958	4,958	4,958
R-squared	0.687	0.689	0.689	0.646	0.647	0.648	0.560	0.560	0.561

Table VIII: Executive Compensation and Product Market Exposure

This table reports results analogous to Table II and III using an alternative definition of afflicted rivals. A rival's exposure to BTD shocks is measured as the number of its projects in BTD-shocked markets divided by its total number of projects. Using this exposure measure, we define afflicted rivals based on their position in the distribution of exposure across all rivals: those in the upper half ("Median"), top third ("Tercile"), or top quartile ("Quartile") of exposure in all years. Panel A replicates the Table II Panel A analysis. Panel B replicates the Table III Panel A analysis. Both panels include the same controls as Table II, as well as firm and year fixed effects. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
	Panel A: Options		
	(1)	(2)	(3)
Year –3	–0.006	–0.028	0.030
	(–0.106)	(–0.426)	(0.392)
Year –2	0.018	0.016	–0.064
	(0.323)	(0.275)	(–1.007)
Year –1	0.044	–0.050	0.006
	(0.905)	(–0.966)	(0.111)
Year +1	0.103**	0.112**	0.120**
	(2.448)	(2.489)	(2.297)
Year +2	0.048	–0.013	0.005
	(1.044)	(–0.251)	(0.086)
Year +3	–0.028	0.014	0.020
	(–0.523)	(0.222)	(0.306)
Observations	5,378	5,378	5,378
	Panel B: Options %		
	(1)	(2)	(3)
Year –3	–0.007	0.000	0.010
	(–0.498)	(0.018)	(0.555)
Year –2	0.004	0.008	–0.006
	(0.323)	(0.592)	(–0.392)
Year –1	0.007	–0.003	0.003
	(0.557)	(–0.204)	(0.211)
Year +1	0.026**	0.034***	0.036***
	(2.202)	(2.632)	(2.642)
Year +2	0.013	0.001	–0.005
	(1.069)	(0.105)	(–0.346)
Year +3	–0.009	–0.013	–0.006
	(–0.689)	(–0.873)	(–0.385)
Observations	5,579	5,579	5,579
R-Squared	0.387	0.387	0.387

Table IX: Risk-Taking and Product Market Exposure

This table reports results analogous to those in Table IV, but based on an alternative definition of afflicted rivals. A rival's exposure to BTD shocks is measured as the number of its projects in BTD-shocked markets divided by its total number of projects. Using this exposure measure, we define afflicted rivals based on their position in the distribution of exposure across all rivals: those in the upper half ("Median"), top third ("Tercile"), or top quartile ("Quartile") of exposure in all years. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Drug Initiation			New Tech initiation			Lengthy Development Initiation		
Rival Definition	Median	Tercile	Quartile	Median	Tercile	Quartile	Median	Tercile	Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year –3	0.013	0.003	–0.012	–0.003	–0.007	0.004	–0.006	0.021	0.026
	(0.457)	(0.093)	(–0.350)	(–0.125)	(–0.237)	(0.110)	(–0.233)	(0.677)	(0.735)
Year –2	0.061	0.042	0.064	0.037	0.027	0.050	0.051	0.032	0.051
	(1.345)	(1.452)	(1.047)	(1.491)	(0.959)	(1.628)	(1.053)	(1.127)	(1.571)
Year –1	–0.010	–0.048	–0.035	0.011	–0.009	0.004	0.035	0.032	0.025
	(–0.381)	(–1.369)	(–1.095)	(0.438)	(–0.322)	(0.136)	(1.449)	(1.169)	(0.823)
Year +1	0.080***	0.089***	0.097***	0.055*	0.066**	0.068***	0.025	0.042*	0.047*
	(3.340)	(2.911)	(3.456)	(1.854)	(2.448)	(2.591)	(0.792)	(1.728)	(1.654)
Year +2	–0.041	–0.043	–0.081	–0.062	–0.057	–0.090	–0.014	0.007	–0.042
	(–1.481)	(–1.365)	(–1.322)	(–1.299)	(–1.617)	(–1.626)	(–0.518)	(0.216)	(–1.235)
Year +3	–0.048	–0.063	–0.035	–0.047	–0.068	–0.071	–0.017	–0.034	–0.013
	(–1.508)	(–1.434)	(–0.898)	(–1.538)	(–1.304)	(–1.476)	(–0.552)	(–0.970)	(–0.324)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,067	5,067	5,067	5,067	5,067	5,067	5,067	5,067	5,067
R-squared	0.443	0.442	0.442	0.511	0.511	0.511	0.457	0.457	0.457

Appendix

Table A1: Executive Compensation Levels Using Ln(1+Options)

The table reports OLS regression results testing the effect of afflicting BTD events on rival firms' CEO compensation. The dependent variable is the natural logarithm of (1 + option award). Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Rival Definition	Median	Tercile	Quartile
	(1)	(2)	(3)
Rival Year –3	–1.083**	–0.779	–0.407
	(–2.111)	(–1.517)	(–0.774)
Rival Year –2	–0.667	–0.373	–0.395
	(–1.490)	(–0.880)	(–0.902)
Rival Year –1	0.001	–0.113	–0.125
	(0.003)	(–0.311)	(–0.315)
Rival Year +1	0.962***	0.943***	0.763**
	(3.196)	(2.946)	(2.277)
Rival Year +2	0.775***	0.544*	0.130
	(2.590)	(1.658)	(0.374)
Rival Year +3	0.299	–0.089	–0.093
	(0.896)	(–0.235)	(–0.241)
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,579	5,579	5,579
R-squared	0.411	0.409	0.408

Table A2: Executive Compensation Tests Using Synthetic Sample

This table replicates the analyses from Tables II and III using a synthetic sample. Each BTD-shocked rival is matched to a control firm that has never experienced BTD entry into any of its operating markets. Matches are to firms of the same size decile and precommercial status. Robust t-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Options %	Stock %	Salary %	Options	Stock	Salary	Total Compensation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post	–0.028*	0.060***	–0.045***	–0.023	0.140**	0.002	0.057
	(–1.887)	(4.016)	(–4.302)	(–0.820)	(2.076)	(0.102)	(1.561)
Post*Treat	0.065***	–0.107***	0.097***	0.093*	–0.429**	0.046	–0.184**
	(2.619)	(–3.879)	(4.482)	(1.691)	(–2.504)	(1.378)	(–2.269)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,168	8,168	8,168	8,168	8,168	8,168	8,168